AN APPROXIMATION-WEIGHTED DETAIL CONTRAST ENHANCEMENT FILTER FOR LESION DETECTION ON MAMMOGRAMS

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Abstract –- **This paper presents a novel approximation-weighted detail contrast enhancement (AWDCE) filter for detecting lesions in digitized mammograms employing the Daub20 wavelet transform. The AWDCE filter is implemented by weighting each pixel in the detail images of chosen levels by the factor that is transformed from corresponding pixel in the approximation image. This ADWCE filter implementation was evaluated with the more traditional methods by using the same publicly accessible database. Experimental results show that the AWDCE filter can automatically enhance the mass contrast while preserving the image details in different scales, and that its performance is better than in previous works, especially in the contrast improvement ratio.**

Keywords –- **Wavelets, contrast enhancement, mammograms**

I. INTRODUCTION

Detection of mass lesions in digitized mammograms becomes difficult when the signal-to-noise ratios of mammographic masses and therefore their contrast as well, defined as the difference in the density values of neighboring structures, are low. To enhance the mass contrast while preserving the gradient-based and texture-based features, which contain much of the information distinguishing masses form the complicated background structures, Peli and Lim[1] introduced the idea of the local contrast modified by the local density, that was further developed by Petrick et al.[2] , as the density-weighted contrast enhancement (DWCE) method. In the DWCE method, the image is first normalized by the rescaling and thresholding transform. The normalized image is next split into a density and a contrast image, respectively. The density image is produced with convoluting the normalized image with a zero-mean Gaussian filter, whose variance is determined empirically. The contrast image is created by subtracting the density image from the normalized image. Since the pixels within the mass are of the high-density values and only the background pixels have generally the low-density values. Multiplying the contrast image by the local density of each pixel will enhance the contrast between masses and their background.

The drawback of the DWCE method is that the variance of the Gaussian filter is defined empirically, and furthermore small variation in the variance may affect the performance of contrast enhancement, since low-contrast structures of different sizes can occur. To overcome this shortage of the DWCE, we develop a novel approximation-weighted detail contrast enhancement (AWDCE) method. This method consists of the multiple level Daubechies wavelet transform instead of the Gaussian filtering, and multiplication of the detail image by the approximation image. Our method can therefore enhance the mass contrast in the different scales and also accelerate the processing.

II. THE AWDCE FILTER

The AWDCE method is described as follows.

Step 1. Perform a rescaling transform on an original image $f(x, y)$ to produce a normalized image $f_n(x, y)$.

Step 2. Perform the 2-dimensional wavelet transform of the normalized image $f_n(x, y)$ to produce a detail image and an approximation image.

Step 3. Perform a nonlinear gray-scale transform of the approximation image to produce a weighting factor image.

Step 4. Multiply the normalized detail image by the weighting factor (a modified approximation image) to produce a modified image.

Step 5. Add the approximation image to the modified image to produce an enhanced image $g(x, y)$.

In the following subsection we describe these steps in more detail.

A. The Rescaling Transform

In order to handle the masses of varying shapes and density values and allow a single set of filter parameters to be applied to all images in the database, we first normalize the original image by the rescaling transform, developed by Petrick et al. [2]. The rescaling transform is defined to be

$$f_n(x, y) = \begin{cases} 0.0 & \text{if } f(x, y) \leq I_{\min} \\ \dfrac{f(x, y) - I_{\min}}{I_{\max} - I_{\min}} & \text{if } I_{\min} < f(x, y) < I_{\max} \\ 1.0 & \text{if } f(x, y) \geq I_{\max} \end{cases} \quad (1)$$

where $I_{\max}$ and $I_{\min}$ are the maximum and minimum of rescaling range, which are set to be the maximum and minimum values containing at least 5% of the total pixel counts.

B. The Daub20 Wavelet Transform

The 2-D wavelet transform is defined by computing running averages and differences via scalar products with the element images called scaling images and wavelets. Like all 2-D wavelet transforms, the 2-D Daub20 wavelet transform

Report Documentation Page

Report Date	Report Type	Dates Covered (from... to)
15 Oct 2001	N/A	-

Title and Subtitle	Contract Number
An Approximation-Weighted Detail Contrast Enhancement Filter for Lesion Detection on Mammograms	Grant Number
	Program Element Number

Author(s)	Project Number
	Task Number
	Work Unit Number

Performing Organization Name(s) and Address(es)	Performing Organization Report Number
Department of Biomedical Engineering Shanghai University Shanghai 200072, China	

Sponsoring/Monitoring Agency Name(s) and Address(es)	Sponsor/Monitor's Acronym(s)
US Army Research, Development & Standardization Group (UK) PSC 802 Box 15 FPO AE 09499-1500	Sponsor/Monitor's Report Number(s)

Distribution/Availability Statement
Approved for public release, distribution unlimited

Supplementary Notes
Papers from 23rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society, October 25-28, 2001, held in Istanbul, Turkey. See also ADM001351 for entire conference on cd-rom., The original document contains color images.

Abstract

Subject Terms

Report Classification	Classification of this page
unclassified	unclassified

Classification of Abstract	Limitation of Abstract
unclassified	UU

Number of Pages
4

of the image $f_n(x, y)$ decomposes the image $f_n(x, y)$ into the subimages a^1, h^1, d^1, and v^1 each have half its rows and columns. Each value of a^1 is equal to an average of a small square (support) containing adjacent values from the image $f_n(x, y)$, hence a^1 is referred to as the first trend subimage. The subimage h^1 is created by computing averages along rows of the image $f_n(x, y)$ followed by computing differences along columns. Consequently, this subimage tends to emphasize horizontal features; it is referred to as the first horizontal fluctuation. The subimages d^1 and v^1, similar to h^1, are referred to as the first diagonal fluctuation and the first vertical fluctuation, respectively.

The Daub20 wavelets have the longest supports, with 1-level wavelets having supports of 20 units, and 2-level wavelets having supports of 58 units, and so on. Consequently, the percentage of Daub20 fluctuation values of the image with significant numbers will be high, due to the large number of Daub20 wavelets whose supports contain a point where a big jump in the pixel's values occurs. A big jump in the pixel's values, being appearances of gradient-based and texture-based features, induces corresponding jumps in the values of the scalar products that define the fluctuation, thus producing fluctuation values with significant numbers.

In terms of multiresolution analysis (MRA) scheme, a k-level Daub20 MRA is:

$$f(x, y) = A^k(x, y) + D^k(x, y) + \cdots + D^1(x, y)$$
$$= A(x, y) + D(x, y) \qquad (2)$$

The approximation image $A^k(x, y)$ is combination of Daub20 scaling images, with the values of the k-level trend subimage as coefficients. The detail image $D^k(x, y)$ is a combination of Daub20 wavelets, with the values of the k-level fluctuation subimages h^k, d^k, and v^k as coefficients. Consequently, the detail image $D^k(x, y)$ reveals gradient-based and texture-based features in the different scale k. There is no analytic rule for determination of the level of MRA. We observe, however, that the Daub20 MRA with 4 levels gives very acceptable results.

C. The Nonlinear Gray-Scale Transformation

The nonlinear gray-scale transformation (NGST) is defined to mapping each pixel in the approximation image $A^k(x, y)$ to a weighting factor, $M(x, y)$, which modifies the corresponding pixel in the detail images $D^k(x, y)$. The NGST consists of applying the following function

$$M(x, y) = \begin{cases} 0.1 & \text{if } 0 \le A^k(x, y) \le 0.25 \\ 0.15 A^k(x, y) + 0.07 & \text{if } 0.25 < A^k(x, y) \le 0.85 \\ 5.33 A^k(x, y) - 4.33 & \text{if } 0.85 < A^k(x, y) \le 0.25 \end{cases} \quad (3)$$

to the approximation image $A^k(x, y)$. The NGST function suppresses the background pixel with low density while retaining the significant breast structures of high density.

D. Multiplication of Detail images and Approximation Image

The multiplication of the detail images and the approximation image is defined by multiplying their values:

$$G(x, y) = M(x, y) \times D_n(x, y) \qquad (4)$$

where $D_n(x, y)$ is the normalized version of $D(x, y)$ by the rescaling transformation defined as (1).

The enhanced image $g(x, y)$ is

$$g(x, y) = A^k(x, y) + G(x, y) \qquad (5)$$

Formulas (3) through (5) are the gist of the AWDCE filter. The rationale is that only the background is generally contained in the low intensity portion of the approximation image $A^k(x, y)$ while masses and other breast structures will be seen at higher intensity values. These detail images $D^k(x, y)$ could be chosen to reflect the different features to different fluctuation levels. Thus, the AWDCE filter can enhance the mass contrast while preserving the image details in different scales.

III. EXPERIMENTAL RESULTS AND DISCUSSIONS

The AWDCE filter was implemented on PC/Windows platform using Visual C++. The AWDCE filter implementation was evaluated with the clinical mammograms obtained from a local hospital and the Mammographic Image Analysis Society (MIAS) database [4], a publicly accessible database.

Fig. 1 shows an example of the AWDCE filtering. The original clinical mammogram was obtained from the files of patients who had undergone biopsy in the Department of Radiology at the Shanghai East Breast Diseases Hospital. The mammograms was acquired using a screen/film system, and was digitized to an original image *3748zl* of 512 pixels by 512 pixels in an 8-bits gray-scale format, shown in Fig.1 (a). Comparing the two images in Fig. 1, we can see that the enhanced image is a shaper image than the original. Particularly interesting is the fact that textural information has been rendered visible in the enhanced image. This improvement in detail visibility is of importance in computer-aided interpretation of mammograms.

The ADWCE filter implementation was also evaluated with the more traditional methods such as both a sigmoid (S-shaped) gray-scale transformation and histogram equalization by using the same database. The sigmoid function used here is defined as[3]:

$$T(D) = \frac{D_m}{2}\left\{1 + \frac{1}{\sin\left(\alpha\frac{\pi}{2}\right)}\sin\left[\alpha\pi\left(\frac{D}{D_m} - \frac{1}{2}\right)\right]\right\} \quad 0 < \alpha < 1 \quad (6)$$

where D is the input gray level, and m is the gray level of region of interest, e.g. masses. The parameter α determines effect of enhancement. The larger the parameter α is, the more seriously the range near m is enhanced.

The effectiveness of image contrast enhancement methods can be quantitatively measured in the following way. The contrast improvement ratio (CIR) of the enhanced image $g(x, y)$ compared with the original image $f(x, y)$ is defined to be[4]

$$CIR = \frac{\sum [g(x, y) - f(x, y)]^2}{\sum f(x, y)^2} \quad (7)$$

In Fig. 2(a) we show an original image *mdb015*. This image was obtained from the MIAS database [5], and was reduced to an image of 512 pixels by 512 pixels in an 8-bits gray-scale format. The enhanced image with the AWDCE is shown in Fig. 2(b), and the enhanced images by the sigmoid transformation and the histogram equalization are shown in Fig. 2(c) and Fig. 2(d), respectively. It is clear from Fig. 2 that the mass in the AWDCE image is shaper than the original image, another instance of effectiveness of the AWDCE filter. Notice also that the AWDCE filter is superior to both of the sigmoid transformation and the histogram equalization in the enhancement of mass contrast. The *CIR* measure confirms this subjective judgement. As shown in the row labeled *mdb015* in Table 1, for the AWDCE filter the *CIR* is 1.5436, which is obviously more than the *CIR* of 0.2013 for the histogram equalization and the *CIR* of 0.0589 for the sigmoid transformation.

Summarizing these examples, we can see that the AWDCE filter was effective for two reasons: (1) the Daub20 wavelet transform was able to decompose the original image into the approximation image and the detail images that reveal gradient-based and texture-based features in different scales, and (2) the NGST function transformed the approximation image by suppressing the background pixel in the low intensity potion retaining the significant breast structures in the high intensity portion.

IV. CONCLUSIONS

This paper presents a novel contrast enhancement technique called the approximation-weighted detail contrast enhancement (AWDCE), based on the Daub20 wavelet transform. We demonstrated the effectiveness of the AWDCE in digitized mammograms and evaluate its performance with the more traditional methods by using a publicly accessible database, the MIAS database. Future research in integration with the conventional methods of segmentation may lead to a new approach for automatic segmentation of mammograms. Clinical application of the AWDCE can improve the visibility in a wide array of medical imaging domains.

V. REFERENCES

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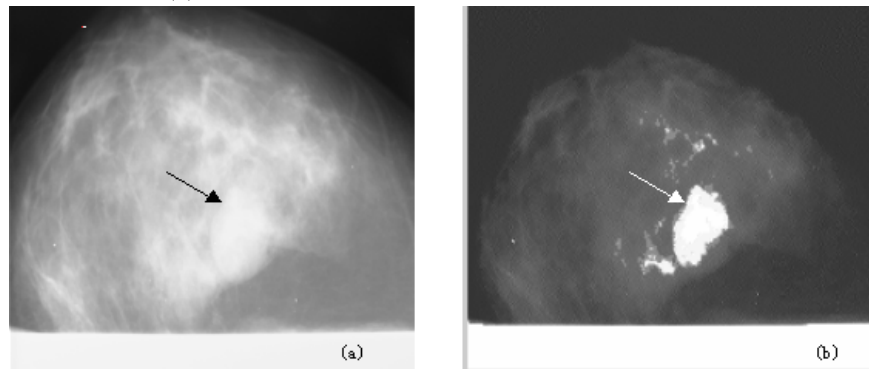
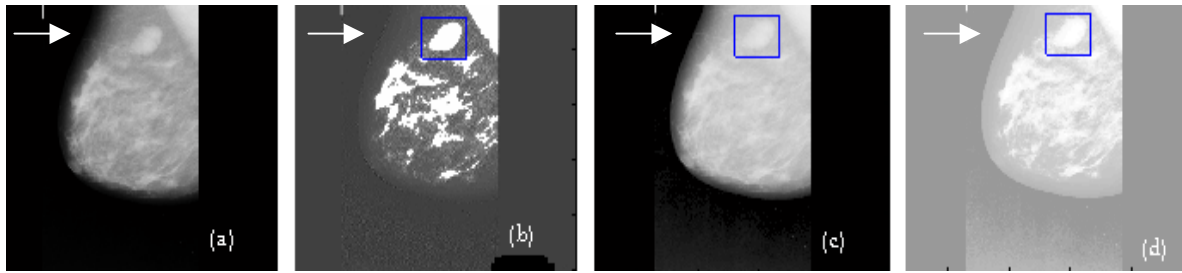Fig.1 (a) Original image (*3748zl*); (b)Enhanced image with the AWDCE.

Fig.2 (a) Original image (*mdb015*); (b)Enhanced image with the AWDCE; (c)Enhanced image with sigmoid transformation; (d)Equalized image.

TABLE 1
CIR measures for images

Image	AWDCE	GST	Histogram Equalization
Mdb010	1.0579	0.0216	0.1742
Mdb015	1.5436	0.0589	0.2013
Mdb025	0.9828	0.0241	0.1654
Mdb054	1.8976	0.1853	0.2549
3748zl	1.2348	0.0283	0.1784